Event-based Indicators for Road Traffic Noise Exposure Assessment

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Summary

Prediction of human response to road traffic noise might be improved by accounting for the occurrence of noise events in addition to using indicators solely based on energy equivalent or percentile measures of noise exposure. Although a wide range of procedures for detecting noise events caused by road traffic have been suggested in literature there is yet no generally accepted algorithm. In this study, we examine the performance of a small selection of noise event detection algorithms, chosen to be representative for a more comprehensive set of algorithms that was compiled on the basis of literature. This selected set of noise event detection algorithms is used to count the number of events occurring within the time history of the road traffic noise level, simulated for a wide range of traffic flow, traffic composition, and propagation distance conditions in unshielded locations in proximity of a roadway. This methodology allows identification of the traffic and distance conditions under which event-based measures provide information about the traffic noise that is uncorrelated with energy-equivalent or percentile measures, and thus may prove useful as supplementary indicators to conventional road traffic noise indicators for use in impact assessment and noise management.

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1. Introduction

Conventional equivalent-energy based indicators may, in some circumstances, be insensitive to the temporal structure of road traffic noise [1], in particular to the noise level maxima caused by individual vehicle passbys. Consequently, the L_{Aeq} and related equivalent energy-based measures may be restricted in their ability to assess and manage road traffic noise in those situations where noise events represent a problem for humans, in terms of sleep disturbance or similar (see for example [2] for an overview of concepts and past findings on noise events and human response to road transport noise). In those situations, it may be required to supplement energy-based indicators with event-based measures. Eventually, human effects research will indicate whether the use of event measures to supplement conventional noise indicators for the assessment of road traffic noise will prove useful in predicting human response—that is, by examining if and how levels and events contribute, independently or in combination, to an association between road traffic noise and human response. However, a necessary condition for any such supplementary measure is that it can only add explanatory power if its relationship with L_{Aeq} is non-monotonic. For example, if a noise event indicator is linearly related to L_{Aeq}, it will not shed any additional light on human response beyond that already estimated from the L_{Aeq} itself. To this end, it is noted that I-INCE suggests, in their exploration of supplementary noise indicators for aircraft noise [3], that a product-moment correlation between L_{Aeq} and an events measure must not exceed 0.5 if the supplementary indicator is to be useful.

In earlier work by the authors [4], a generalized algorithm for detecting and counting the number of noise events caused by road traffic is described. This generalized algorithm is based on the traffic noise level exceeding either a fixed or an adaptive threshold—the latter being either the L_{Aeq}, L_{A50} or L_{A90} of the sound signal. By varying the threshold, emergence and minimum time gap between successive events, a wide range of parameter sets was considered for detecting noise events caused by road traffic as it is heard indoors, for window-open and window-closed conditions. The performance of this generalized detection algorithm was then investigated through a systematic simulation study in which the time history of noise levels is modelled for a extensive range of noise exposure scenarios that can occur in practice.

In Section 2 of this paper, the methodology and the selection of representative algorithm parameter sets are briefly recapitulated (we refer to [4] for full details). Subsequently, this paper reports on the relationship between the number of detected noise events, using the selected set of algorithm parameters, and the L_{Aeq} (Section 3.1 and 3.2), and on the traffic flow and propagation distance conditions under which the use of supplementary event detection measures for road traffic noise may be appropriate (Section 3.3).

2. Simulation methodology

2.1. Simulation of instantaneous sound level

A modelling approach was adopted to create time histories of the noise level caused by road traffic for a range of likely scenarios—something that would be largely impractical using data gathered through field measurements. The instantaneous sound level in free field caused by road traffic was simulated using the Noysim2 model described in [5]. This model combines a microscopic simulation of road traffic (TSS Aimsun) with an instantaneous vehicle noise emission model, and a point-to-point sound propagation model (ISO 9613). The vehicle noise emission model is based on the Imagine model [6], and accounts for the distribution in sound power emitted by individual vehicles within different categories, through a per-vehicle correction [5]. For the purpose of this work, the output of Noysim2 consists of the time history of the instantaneous A-weighted sound level at the location of the receiver.

2.2. Noise exposure scenarios

A receiver adjacent to a straight dual-lane roadway carrying free flow traffic is considered, and traffic flow variables and the propagation distance from roadway to receiver are varied to cover a full range of realistic values. Table I shows an overview of the selected parameter ranges; the total number of unique traffic flow/distance scenarios considered to represent the population of acoustic conditions found near roadways equals 500. The duration of each simulation was set at 1 h, with a timestep of 125 ms. For each scenario, the simulation was replicated 30 times, such that the variance between different runs could be accounted for.

Table I. Ranges for the variables used to construct the exposure scenarios.

Variable	**Range**
Speed limit of the road [km/h]	60, 100
Traffic demand [vehicles/h]	5, 10, 20, 50, 100, 200, 500, 1000, 2000, 5000
Amount of heavy vehicles [%]	0, 10, 20, 50, 100
Distance to the roadway [m]	7.5, 15, 30, 60, 120

Figure 1 shows the distribution of $L_{\mathrm{Aeq,1h}}$ generated by the 500 modelled scenarios, plotted in bands with a width of 2 dB(A). The range extends from just under 34 dB(A) to near 84 dB(A). Counts in any one band may result from very different scenarios: either, e.g., from high traffic flows at considerable distance, or from low flows but at a close distance.

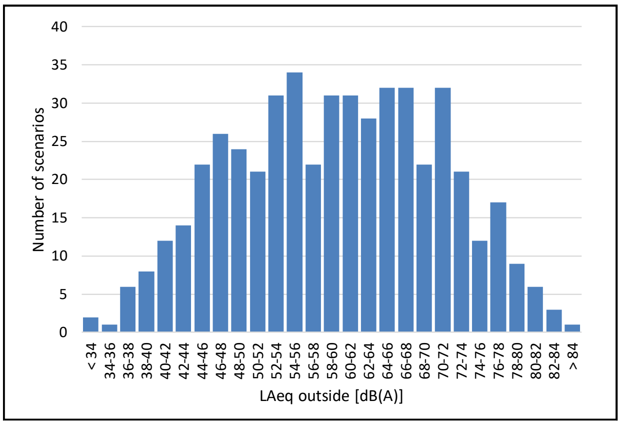

Figure 1. Distribution of the free-field $L_{\mathrm{Aeq,1h}}$ for the 500 noise exposure scenarios.

In order to relate the simulated outdoor noise level time histories to noise exposure limits for sleep disturbance, which are typically based on indoor levels, the dwelling attenuation has to be taken into account. The latter is critically dependent on the state of closure of windows in the sleeping room, as well as on human behavior with respect to window operation, and there is likely to be a significant difference between summer and winter, tropical and temperate climates etc. For the purpose of this study, two extreme conditions for building envelope attenuation are considered: fully opened and fully closed windows, by applying an outside to inside attenuation of 5 dB(A) and 25 dB(A) respectively—values were selected based on a scan of the literature as discussed in [4].

2.3. Noise event detection algorithm

Individual events in the time history of the traffic noise are identified using a generalized exceedance-based detection algorithm, that was constructed on the basis of an extensive literature review, reported in [4]. With this algorithm, the onset of a noise event is detected when the instantaneous sound level exceeds a threshold level L_β with an emergence of at least E. Noise events are only retained when the time gap (or noise free interval) since the previous event is larger than τ_g.

An extensive range of alternative sets of values for the parameters L_β, E and τ_g of the generalized exceedance algorithm was then utilized to detect and count noise events in the simulated time histories. For the detection threshold L_β, both the fixed case and the adaptive case was considered. Fixed thresholds varied from 45 dB(A) to 75 dB(A) in steps of 5 dB(A). The emergence E was set to zero in the case of fixed thresholds. Adaptive thresholds considered were L_{Aeq}, L_{A50} and L_{A90} (calculated over the 1h simulation duration), in combination with 3, 5, 10 and 15 dB(A) as minimum emergences E above L_β. Four alternatives were used for the minimum time gap τ_g between events: 3, 5, 10 or 30s. Finally, the detection algorithm was applied both to the open-window and closed-window simulations; this resulted in 152 different parameter sets (19 combinations of L_β and E, with 4 values of τ_g, and applied either to the open-window or closed-window simulation).

2.4. Algorithm parameter set selection

There are at least two *a priori* criteria that any event detection algorithm must meet: *validity* (is the number of events detected with the algorithm reasonable?) and *reliability* (does the algorithm produce consistent counts?). On the one hand, validity was assessed by considering the mean number of noise events detected by the generalized algorithm across all 500 traffic flow/distance scenarios, with each of the 152 parameter sets. This mean number ranged from almost none up to 77 noise events per hour. To have face value as a potential indicator, an algorithm needs to detect events for many (not necessarily all) of the possible scenarios, and should result in sufficient variation in the number of events detected as the traffic flow and/or the distance to the road changes. On the other hand, reliability was assessed by examining the variation in the number of events detected across the 30 simulation replications for each scenario. Standard deviations ranged from 0.3 to 9.4 events across all algorithm parameter sets. Both validity and reliability criteria resulted in the exclusion of 107 of the potential algorithm parameter sets; 45 prospective parameter sets were retained.

Subsets of the retained parameter sets still exhibited a considerable redundancy in their counts of noise events. Categorical Principal Component Analysis (CATPCA), a statistical data reduction technique, was therefore applied to identify a smaller, more manageable subset of the 45 valid and reliable algorithm parameter sets. Seven clusters of parameter sets were identified; Table II gives an overview of seven prototypical parameter sets, one selected out of each cluster, together with the labels used in the remainder of this paper.

Table II. The 7 selected prototypical algorithm parameter sets, together with the naming convention.

Label	L_β	E	τ_g	Window
NA50	50 dB	0 dB	5s	opened
NA55	55 dB	0 dB	5s	opened
NA65	65 dB	0 dB	5s	opened
NA70	70 dB	0 dB	5s	opened
NAL50E03	L_{A50}	3 dB	5s	closed
NAL50E10	L_{A50}	10 dB	5s	opened
NALEQE03	L_{Aeq}	3 dB	30s	opened

Six of the parameter sets identify noise events as detected inside the dwelling with windows open, one parameter set (NAL50E03) identifies noise events as detected inside the dwelling with windows closed. We refer to [4] for more details on the algorithm parameter selection procedure.

3. Number of detected events and L_{Aeq}

3.1. Events detected across acoustic conditions

The results of applying the seven parameter sets to the generalized detection algorithm for detecting noise events within the time histories of road traffic noise generated by the 500 traffic/distance conditions are shown in Figures 2 and 3. The figures plot the mean number of noise events detected using each parameter set against L_{Aeq}; the mean is calculated across those scenarios which result in an L_{Aeq} within each of the 2 dB(A) bands of exposure.

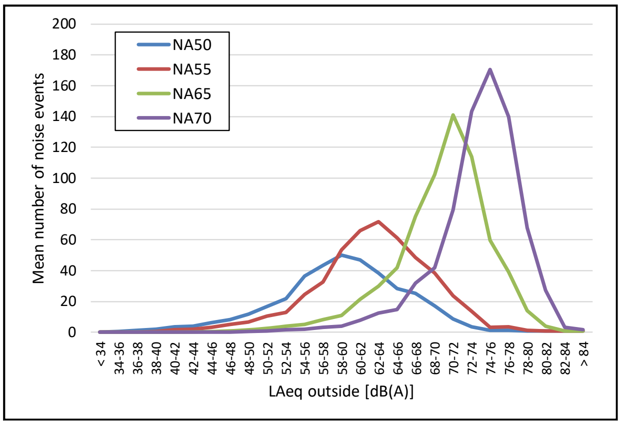

Figure 2. Mean number of noise events for each 2 dB(A) band of L_{Aeq} (outside the dwelling) across the 500 scenarios, for the fixed threshold parameter sets.

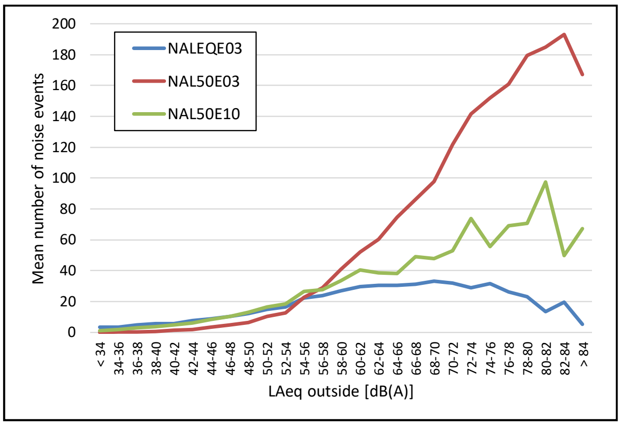

Figure 3. Mean number of noise events for each 2 dB(A) band of L_{Aeq} (outside the dwelling) across the 500 scenarios, for the adaptive threshold parameter sets.

The number of noise events detected using each of the fixed exceedance open-window parameter sets has a Gaussian distribution on L_{Aeq}. The number of noise events detected using the adaptive threshold parameter sets based on L_{A50} have very different relationships with L_{Aeq}, with the mean number of noise events tending to increase monotonically with L_{Aeq}. The L_{Aeq}-based adaptive threshold parameter set results in a distribution more like those of the fixed threshold parameter sets, but much flatter and with a lower number of noise events detected.

Visual examination of Figures 2 and 3 shows non-monotonic relationships between L_{Aeq} and the mean number of noise events detected by the four fixed-threshold parameter sets and by the NALEQE03 parameter set. The mean number of noise events detected using both the L_{A50}-based adaptive thresholds in Figure 3 increases consistently with L_{Aeq} up to levels above 80 dB(A), thus these two algorithm parameter sets nominally fail the non-monotonicity test required for an event-based indicator to supplement the energy-based indicator. However, the spread of the number of events about the mean (not shown) for the NAL50E10 parameter set is so large that particular values of the number of noise events in individual scenarios could be associated with many different values of L_{Aeq}.

Table III shows the correlation between L_{Aeq} outside the dwelling, and the number of noise events detected inside. The NA50, NA55 and NAL50E10 parameter sets result in low correlations with L_{Aeq}, indicating that these measures can provide useful supplementary information beyond that provided by L_{Aeq}. The NA65 and NA70 fixed parameter sets, and the other two adaptive parameter sets, NAL50E03 and NALEQE03, have high rank order correlations with L_{Aeq}, suggesting that they would not be useful as supplementary indicators. Only NA50, NA55 and NAL50E10 meet the I-INCE criterion [3] that the product-moment correlation with L_{Aeq} must not exceed 0.5, and are thus primary candidates for further consideration as event-counting indicators.

Table III. Correlation between L_{Aeq} outside the dwelling and the number of events detected inside the dwelling, for the 7 selected algorithm parameter sets.

Label	**Spearman's rank corr. coefficient**	**Pearson corr. coefficient**
NA50	-0.244	0.003
NA55	0.123	0.216
NA65	0.787	0.573
NA70	0.868	0.628
NAL50E03	0.917	0.824
NAL50E10	0.384	0.454
NALEQE03	0.633	0.611

The different parameter sets result in algorithms that have distinctly different ranges of L_{Aeq} over which they detect events. This accords with the interpretation in the CATPCA analysis [4] that several groups of fixed-threshold algorithms are associated with lower overall levels of road traffic noise and that some are associated with high overall levels. The adaptive-threshold parameter sets result in an algorithm that detects events across the full range of L_{Aeq}, but with far fewer events detected at levels below 50 dB(A). Anecdotally, events in road traffic streams are seen to be an issue in terms of human response at lower levels of road traffic noise—for example at night when traffic flows and overall levels are lower, with noisier vehicles heard above these lower levels. This would suggest that it may be appropriate to adopt algorithms (NA50, NA55) that detect events in traffic noise signals at least at the low end of the L_{Aeq} scale.

3.2. Relationship with L_{Aeq}

A more detailed view of the relationships between the number of noise events detected and the L_{Aeq} across the 500 traffic/distance scenarios is shown in Figure 4. The panels plot the number of noise events as they would be detected inside a dwelling with open windows for all traffic flows modelled, with separate panels for different distances from the roadway, against the outside L_{Aeq}.

The L_{Aeq} is, as would be expected, linearly related to the logarithm of traffic flow, and decreases with increasing distance from the roadway. For clarity, the effects of variation in the percentages of heavy vehicles and in the traffic speed on the indicators is not shown. Figure 4 confirms the observation above that NA50 and NA55 both have distinct non-monotonic relationships with L_{Aeq}, and are potential supplementary indicators. The algorithms based on these parameter sets detect events from the lowest traffic flows up to traffic flows of 1,000 to 2,000 vehicles per hour, with no events detected at higher flow rates. Both indicators also detect events at all the distances modelled, with decreasing numbers of events as the distance from the roadway increases.

Figure 4 also confirms the observation above that NAL50E10 also has a non-monotonic relationship with L_{Aeq}, and thus may also be a potential supplementary indicator. It detects events across the full range of traffic flows, with the maximum number occurring at flow rates of 500 to 2,000 vehicles per hour. But unlike the NA50 and NA55, the maxima occur at lower flow rates as distance from the roadways increases. The number of noise events also decreases with distance.

The conclusion from examination of Figure 4 is that the NA50, the NA55 and the NAL50E10 parameter sets can all be considered for practical application as event detection indicators, with the primary difference being that the NAL50E10 detects the maximum number of noise events at higher traffic flow rates, but with the maxima occuring at increasingly lower flow rates as the distance from the roadway increases. All detect noise events heard indoors with the windows of the dwelling open.

3.3. Relevant traffic and distance scenarios

In Figure 4(a) it can be seen that, at the closer distances to the roadway, events above 50 dB(A) (NA50) are detected at the very lowest traffic flows,

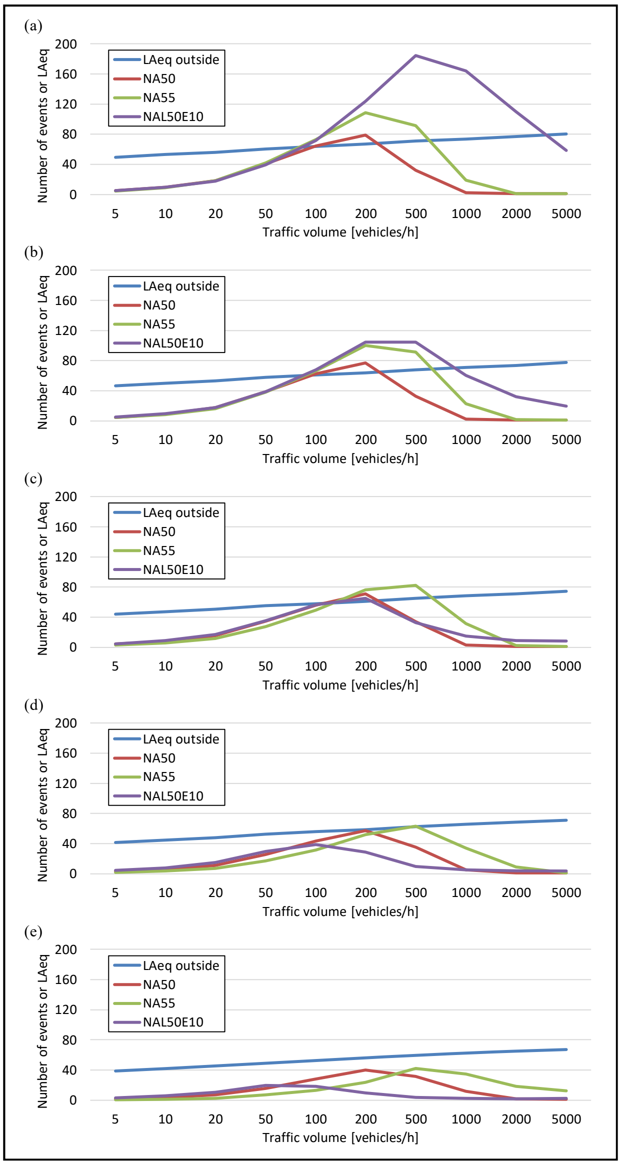

Figure 4. Comparison of outdoor L_{Aeq} with NA50, NA55 and NAL50E10 as a function of traffic volume, for different distances to the roadway: (a) 7.5m, (b) 15m, (c) 30m, (d) 60m, (e) 120m.

increasing to a maximum around 200 vehicles/hour, then decreasing rapidly to zero at between 500 and 1,000 vehicles/hour. The increase in NA50 as traffic flow increases from the lowest flows indicates that every passing vehicle triggers the NA50 algorithm. Above 200 vehicles/hour the NA50 peaks and then starts to decrease, which is explained by the smaller vehicle headways at these flow rates, resulting in the “filling in” of the traffic noise signal as the gap between successive vehicles decreases [7]. This results, at about 1,000 vehicles/hour, in the NA50 algorithm detecting zero events, because the indoor traffic noise signal (with windows open) never drops below the detection threshold of 50 dB(A). This transition occurs at lower vehicle flow rates.

The number of events detected using the NA50 parameter set lowers with increasing distance from the roadway, as can be seen in Figure 4 panels (b) to (e). At the largest distance modelled (120 m), the NA50 no longer detects events at flow rates below about 100 vehicles/hour, because most vehicles do not produce high enough levels at these distances to trigger an event.

The equivalent results for the NA55 parameter set tend to follow the same pattern as the NA50 across most of the scenarios, but with a somewhat greater number of events detected at any given scenario, and with the distributions of the number of events translated to slightly higher traffic volumes.

Furthermore, Figure 4 shows that the use of the adaptive threshold algorithm parameter set NAL50E10 results, at close distance, in the detection of a higher number of noise events than either NA50 or NA55. Events are detected across all traffic flow rates, but with a very flat Gaussian distribution with some negative skewness. At larger distance, the maximum number of events detected is much lower, and occurs at lower traffic flow rates as compared to the fixed threshold parameter sets with increasing distance from the roadway. This would appear to be due to the adaptive characteristic of this algorithm, with the L_{A50} dropping with increasing distance from the roadway, but with the maxima from individual vehicles dropping even more because these levels attenuate according to point source spreading. As a result, the NAL50E10 decreases with distance. It is not intuitively obvious why this effect of distance is so strongly dependent on traffic flow.

4. Summary

This paper reported on the progress within a project to determine suitable algorithms for the detection of noise events caused by road traffic. The use of noise event measures to supplement conventional noise indicators such as L_{Aeq} for management of road traffic noise will, in the end, have to be assessed through human effects research. This will entail examining if and how levels and events contribute, independently or in combination, to an association between road traffic noise and human response. Although there are indications, both from sleep research and from other studies of human effects of noise, that human response may also depend on noise events as well as on level, there is no agreement as yet as to how noise events should be measured.

In earlier work, a generalized exceedance-based algorithm for the detection of noise events caused by road traffic was investigated, resulting in a relatively large number of alternative parameter sets, even after those that result in unreliable or unreasonable numbers of events are identified. The present work reported the performance of a concise subset of these alternative parameter sets. It was found that NA50 and NA55, detecting the number of events exceeding 50 dB(A) and 55 dB(A) respectively, and NAL50E10, detecting the number of events exceeling L_{A50} with at least 10 dB(A), can all be considered for practical application as event detection measures. All three apply to the detection of noise events heard indoors with the windows of the dwelling opened. This finding is based on the assumption that, for any such supplementary measure, its relationship with L_{Aeq} is non-monotonic.

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